Deciphering Liquidity Risk on the Istanbul Stock Exchange

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Abstract

This paper examines the impact of illiquidity and liquidity risk on expected stock returns in the Turkish stock markets. Using daily data of the ISE-100 stock index from 2005 to 2012 and Amihud (2002) illiquidity measure, we test the liquidity-adjusted capital asset pricing model (L-CAPM) of Acharya and Pedersen (2005). Performing cross-sectional regression tests across test portfolios, we find supporting evidence that illiquidity is significantly and positively priced. Specifically, our results indicate that liquidity risk arising from the commonality in liquidity is the most important component of liquidity risk. The strong interrelationship between the market liquidity and the liquidity of individual stocks suggests that market-wide shocks on the Istanbul Stock Exchange might quickly affect every stock in this market. Hence, liquidity commonality might create a systemic risk in which case liquidity shocks can be perfectly correlated across all stocks.

Our study is the first to investigate stock liquidity-return relationship at daily frequency and to apply the L-CAPM on the Turkish stock markets. Our findings provide interesting conclusions for investors, risk managers and regulators in emerging economies, and in particular, Turkey. Investors should incorporate liquidity risk into their trading and hedging strategies to improve their risk profile and increase their investment returns. Furthermore, an improved understanding of systemic liquidity is vital for regulatory authorities to design improved regulations against systemic shocks.

Keywords: Liquidity risk and asset pricing; stock returns; Liquidity-adjusted CAPM; illiquidity premium; Istanbul Stock Exchange.

Jel Classification: C30, G12

1. Introduction

Standard asset pricing models are based on the assumption of *frictionless* (perfectly liquid) markets, where every security can be traded at no cost all the time and agents are *price-takers*. However, real markets are not frictionless, and they are subject to *liquidity* risks. Considering liquidity in asset pricing is crucial, since it affects an investor's trading strategy and portfolio performance. Amihud and Mendelson (1986) are one of the first to examine the linkage between stock return and stock liquidity, and to report that investors require return compensation for illiquidity. There also exists extensive theoretical and empirical literature that shows that liquidity risk affects asset returns (Chordia, 2001; Pastor and Stambaugh, 2003; Acharya and Pedersen, 2005; Bekaert, 2007; Lee; 2011). The idea is that risk-averse investors require compensation for investing in illiquid securities.

During the recent financial crisis, asset markets experienced a liquidity freeze; bid-offer spreads widened, and the cost impact of trades became large as market makers charged higher prices for providing liquidity. As the subprime meltdown hit in 2007, many financial institutions found that the structured-credit market almost completely dried up, and that it was almost impossible to liquidate positions in asset-backed-securities. Hence, the problem of illiquidity has become one of the greatest challenges and problems faced by financial industry in the last decade. Since the recent financial crisis, the concept of liquidity has gained considerable attention from both economists and regulators, leading to a rising number of models and empirical work.

The purpose of this study is to investigate the impact of illiquidity and liquidity risk on asset returns in the Turkish equity markets. We utilize daily Turkish stock price-volume data in ISE-100 during 2005-2012 and test the liquidity-adjusted capital asset pricing model (L-CAPM) of Acharya and Pedersen (2005). L-CAPM provides a unified framework to explore the impact of liquidity on asset returns through various channels: commonality in illiquidity with the market illiquidity, return sensitivity to market illiquidity, and illiquidity sensitivity to market returns.

Following the methodology in Acharya and Pedersen (2005), we estimate an unconditional version of L-CAPM using portfolios sorted on past year's illiquidity. To measure illiquidity, we choose the price impact measure of Amihud (2002). Stock illiquidity is defined here as the ratio of the daily absolute return to dollar volume. In order to capture the time variation in liquidity risk, we also estimate the conditional L-CAPM. Specifically, we use the multivariate GARCH (Diagonal VECH) model to estimate the conditional time-varying covariances. In each model, we perform pooled cross-sectional regressions across the test portfolios and identify the significant risk factors in the Turkish market.

This paper contributes to the literature in several respects. First, the importance of liquidity in asset pricing has not yet been widely analyzed in the Turkish equity markets. We take a step in filling the gap in empirical literature. Furthermore, this is the first study that tests the L-CAPM at daily frequency on the Istanbul Stock Exchange. Turkey has one of the fastest growing economies, and one of the most developed equity markets among the emerging countries. With rising global interest for emerging markets, Turkey attracts a growing number of domestic and global investors. Understanding the liquidity structure of the Turkish equity markets is important in order to design effective investment strategies and keep up with foreign investor's participation. The rest of the paper is structured as follows. Section 2 reviews the previous literature and Section 3 explains the L-CAPM methodology. Section 4 presents the empirical results and Section 5 concludes.

2. Literature Review

An extensive amount of empirical literature finds that liquidity risk plays a significant role in asset pricing. Employing different liquidity proxies, these studies show that expected stock excess returns reflect an illiquidity premium. The empirical work estimates the existence and magnitude of a liquidity effect either cross-sectionally, comparing the returns of individual assets with different levels of liquidity, or in a time-series study, where the security's return is related to time-varying liquidity. Some researchers investigate the sensitivity of asset returns to individual liquidity measures, while others examine whether exposure to market-wide aggregate liquidity is priced. Regardless of the proxy, the empirical evidence unanimously supports the existence of liqudity effect in asset pricing.

The first question addressed by researchers was the *existence* of an illiquidity premium, first investigated by Amihud and Mendelson (1986). Using NYSE and AMEX stock returns and bid-ask spreads over the period 1961-1980, they demonstrate that expected asset return is an increasing function of illiquidity. The impact of illiquidity is revisited for NYSE stock returns by Amihud and Mendelson (1989), Brennan and Subrahmanyam (1996) and Brennan et al. (1998). Their findings confirm an increasing relationship between returns and illiquidity. In the same direction, researchers develop new proxies for illiquidity and re-analyze the illiquidity-return relationship in the U.S. stock markets. For example, Amihud (2002) develops a new measure of illiquidity related to Kyle (1985) λ and finds that NYSE stock returns are positively related to expected market illiquidity during 1963-1996. Similarly, Hasbrouck (2009) proposes a Gibbs estimate for trading cost and demonstrates that it is positively related to U.S. equity returns during 1926-2006.

Departing from earlier studies, Acharya and Pedersen (2005) build a liquidity-adjusted CAPM (L-CAPM), providing a unified framework to explore liquidity and liquidity risk. They employ a measure of illiquidity developed by Amihud (2002) and test their model for NYSE/AMEX stocks during 1964-1999. Their results indicate that excess returns are positively and significantly related to portfolios' illiquidity and illiquidity risk. Following their findings, several studies test the L-CAPM in various markets. Bekaert et al. (2005) extend L-CAPM (2005), allowing for separate effects for market and liquidity risks on local and global scales. Their results suggest that local liquidity risk remains the most important priced factor. In a similar direction, Lee (2011) empirically tests the L-CAPM on a global scale and shows that as a country becomes more open, global liquidity risk becomes more important than local liquidity risk. More recently, Minović and Živković estimate the conditional L-CAPM for Serbian stock data for 2005-2009 and find that liquidity risk significantly impacts asset prices. Similarly, Hangströmer et al. (2011) test the conditional L-CAPM for NYSE and AMEX data for 1926-2010 and show that asset illiquidity exposure to market returns is the most important component of illiquidity risk.

Recent studies also analyze illiquidity as an important *risk factor* and examine whether illiquidity risk has a *systemic* component. For example, Brockman et al. (2009) conduct a global study of commonality in liquidity using intraday spread and depth data from 47 stock exchanges. They show that firm-level changes in liquidity are significantly influenced by exchange-level changes across most of the world's stock exchanges. They also find evidence of a global component in liquidity commonality which is driven by U.S. macroeconomic announcements. Conversely, Sadka and Lou (2011) show that liquid stocks underperformed illiquid stocks during the 2008-2009 financial crisis, and argue that the performance of stocks during the crisis can be better explained by their historical liquidity risk than by their historical liquidity levels. Finally, Karolyi et al. (2012) examine the sources of commonality in liquidity across 40 stock markets. Their findings suggest that commonality in liquidity is greater during times of high market volatility and in greater presence of international investors.

3. Methodology

3.1. Constructing a Liquidity Measure

Liquidity is an elusive variable that has several dimensions, and there exists no unique measure that can capture all its characteristics. Bien et al. (2006) explain that liquidity encompasses the properties of immediacy, depth, tightness, and resiliency. Immediacy represents the possibility to trade an asset quickly without perturbing its value, while depth indicates the total number of units available to buy or sell at the quoted price. Similarly, tightness measures the cost of trading a position and resiliency is the speed with which the price of an asset after a large trade returns to its fundamental value. Therefore, the greater the sensitivity of an asset to order flow, the larger is the liquidity. Although liquidity cannot be directly measured, there exist many proxies. These proxies can be classified as microstructure and low-frequency measures.

The bid-ask spread is based on microstructure data and measures the cost of executing small trades. It is calculated as the difference between the bid and offer price divided by the bid-ask midpoint. Copeland and Galai (1983) argue that market-makers optimize their positions by setting bid-ask spreads which maximize the difference between their expected revenues from liquidity-motivated traders and expected losses to unidentified informed traders. Thus, the bid-ask spread compensates market-makers for inventory costs, order processing fees, and informational disadvantage. This measure is with high precision, but high-frequency data are often not available for long periods of time. For this reason, low-frequency proxies for liquidity have been developed.

The low-frequency liquidity measures consist of a large number of proxies, such as stock-turnover, volume, Lesmond, Ogden, and Trzcinka (1999) zero-return proportion, Amihud illiquidity ratio (2002), and Pastor and Stambaugh (2003) return reversal, among others. In this paper, we follow Amihud (2002) in estimating liquidity of a stock. The *Illiquidity Ratio of Amihud* (2002) is defined to be the absolute percentage price change per dollar of trading volume. The monthly illiquidity ratio of a stock i in month t is

$$ILLIQ_{i,t} = \frac{1}{Days_{i,t}} \sum_{d=1}^{Days_{i,t}} \frac{|r_{i,d,t}|}{v_{i,d,t}} \tag{1}$$

where $r_{i,d,t}$ and $v_{i,d,t}$ are the return and dollar volume on day d in month *t*, respectively. $Days_{i,t}$ is the number of observations in month t for stock i. This measure follows from Kyle's concept of illiquidity (the response of price to order flow) and reflects a stock price's sensitivity to large trades. An illiquid stock with a high value of $ILLIQ_{i,t}$ moves a lot in response to little volume.

There are several reasons why we choose Amihud (2002)'s measure in this paper. First, there exist previous empirical studies that confirm this measure as valid liquidity instrument. Hasbrouck (2002) finds that Amihud's measure is most highly correlated with trade-based measures. Similarly, Goyenko, Hoden and Trzcinka (2009) compares several measures of liquidity and conclude that Amihud's measure yields significant results in capturing the price of trade. Moreover, Acharya and Pedersen (2005) test the validity of their L-CAPM with Amihud's measure. Replicating their methodology enables us to compare our study with theirs, and to understand whether liquidity channels under the L-CAPM act differently in Turkey compared to the U.S.

3.2. Liquidity-Adjusted Capital Asset Pricing Model (LCAPM)

Acharya and Pedersen (2005) extend the CAPM to a framework where a security's liquidity risk affects its expected return. They assume an overlapping generations economy in which a new generation of risk-averse agents is born at any time $t \in \{\ldots, -2, -1, 0, 1, 2, \ldots\}$ and maximize their expected utility at *t+1*. The illiquidity cost C_t^i—which is the per-share cost of selling security i—varies over time. This means that investors are uncertain about what their transactions cost when they trade a security. Investor's uncertainty about illiquidity cost is what creates *the liquidity risk* in this model. Specifically, Acharya and Pedersen model a security's net return as the price change plus dividend minus illiquidity cost. Rewriting the CAPM, they derive the conditional expected return of a security in equilibrium:

$$E_t\left[r_{t+1}^i - r^f\right] = E_t\left[c_{t+1}^i\right] + \frac{cov_t(r_{t+1}^i - c_{t+1}^i, r_{t+1}^m - c_{t+1}^m)}{var_t(r_{t+1}^m - c_{t+1}^m)} E_t[r_{t+1}^m - c_{t+1}^m - r^f] \tag{2}$$

where r^f is the risk-free rate.

Equivalently, equation (2) can be rewritten as:

$$\begin{aligned} E_t\left[r_{t+1}^i - r^f\right] = E_t\left[c_{t+1}^i\right] + \lambda_t \frac{cov_t\left(r_{t+1}^i, r_{t+1}^m\right)}{var_t(r_{t+1}^m - c_{t+1}^m)} + \lambda_t \frac{cov_t\left(c_{t+1}^i, c_{t+1}^m\right)}{var_t(r_{t+1}^m - c_{t+1}^m)} \\ - \lambda_t \frac{cov_t\left(r_{t+1}^i, c_{t+1}^m\right)}{var_t(r_{t+1}^m - c_{t+1}^m)} - \lambda_t \frac{cov_t\left(c_{t+1}^i, r_{t+1}^m\right)}{var_t(r_{t+1}^m - c_{t+1}^m)} \end{aligned} \tag{3}$$

$$= E_t\left[c_{t+1}^i\right] + \beta_t \lambda_t + \beta_t^{L1} \lambda_t - \beta_t^{L2} \lambda_t - \beta_t^{L3} \lambda_t$$

where

$$\lambda_t = E_t[r_{t+1}^m - c_{t+1}^m - r^f] \tag{4}$$

$$\beta_t = \frac{cov_t\left(r_{t+1}^i, r_{t+1}^m\right)}{var_t(r_{t+1}^m - c_{t+1}^m)} \tag{5}$$

$$\beta_t^{L1} = \frac{cov_t\left(c_{t+1}^i, c_{t+1}^m\right)}{var_t(r_{t+1}^m - c_{t+1}^m)} \tag{6}$$

$$\beta_t^{L2} = \frac{cov_t\left(r_{t+1}^i, c_{t+1}^m\right)}{var_t(r_{t+1}^m - c_{t+1}^m)} \tag{7}$$

$$\beta_t^{L3} = \frac{cov_t\left(c_{t+1}^i, r_{t+1}^m\right)}{var_t(r_{t+1}^m - c_{t+1}^m)} \tag{8}$$

Equation (3) states that the required excess return of a security is the expected liquidity cost, plus four covariances times the risk premium. As in the standard CAPM, excess return of a security increases linearly with the covariance between the asset's return and the market return. At the same time, the illiquidity cost terms c_{t+1}^{i} and c_{t+1}^{m} give rise to three additional types of liquidity risk:

1. $cov_t(c_{t+1}^{i}, c_{t+1}^{m})$: The covariance between the asset's illiquidity and the market illiquidity represents commonality in liquidity and affects required returns positively. Investors require a return premium for assets that become illiquid when the market becomes illiquid. Empirical support for this effect has been provided by Chordia et al. (2000), Hasbrouck and Seppi (2001), and Huberman and Halka (1999).
2. $cov_t\left(r_{t+1}^{i}, c_{t+1}^{m}\right)$: The covariance between a security's return and the market liquidity affects required returns negatively. Investors accept a lower return for assets that give high returns when the market becomes illiquid. This effect has been documented by Sadka (2002), Wang (2002) and Pastor and Stambaugh (2003).
3. $cov_t(c_{t+1}^{i}, r_{t+1}^{m})$: The third risk arises from the covariance between a security's illiquidity and the market return. Investors accept a lower expected return on a security that stays liquid in a down market. Ljungqvist and Richardson (2003) present evidence for this effect.

The model further demonstrates that a persistent negative shock to a security's liquidity leads to low contemporaneous returns and high predicted future returns. Overall, it provides a unified framework for testing the effect of liquidity risk on asset prices. Acharya and Pedersen (2005) show that liquidity is persistent over time, and that it predicts future returns.

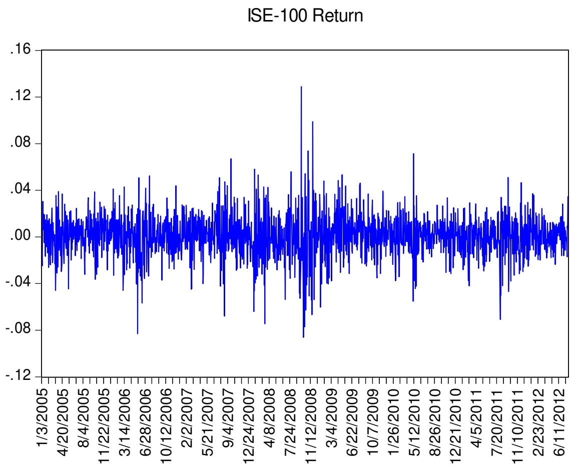
4. Empirical Results

4.1. Data

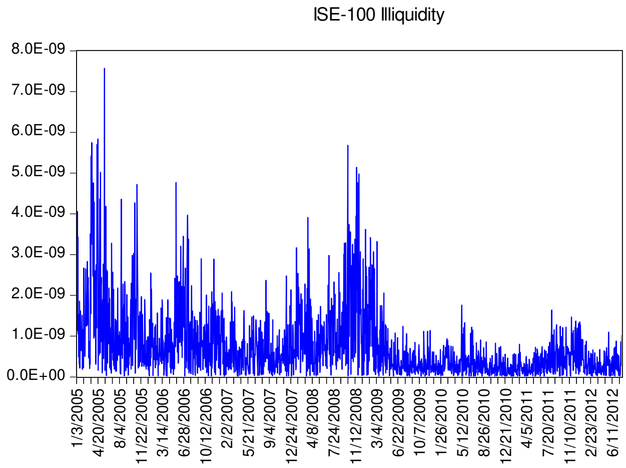
We employ daily return and volume data of the common stocks traded in ISE-100 (Istanbul Stock Exchange) index from January 2005 to July 2012. As the market proxy, we take the ISE-100 index, which is a price and total return index weighted by the market value of shares outstanding. The overnight Turkish Lira Reference Interest Rate (TRLibor) is used as the risk-free rate, and it represents the reference interest rate to be used in transactions among the banks in Turkey. The data set is obtained from *Matriks Data Terminal* and includes 1909 observations for each stock.

The ISE-100 consists of the 100 largest and most liquid companies listed on the National Market. It automatically covers ISE-30 and ISE-50 stocks. According to the figures published by *TKPAKB*, there are 237 companies traded on the National Market as of January 2012. Specifically, we focus on the ISE-100 index because it is considered to be the main indicator of the Turkish equity markets and represents more than three forths of the market in terms of trading volume. Liquidity (trading volume and number of traded shares) criteria are reviewed quarterly, and the index composition can be modified. This study employs the stocks that are listed in the ISE-100 as of 26 July, 2012.

Daily returns are calculated as percentage change in closing price, and *the Illiquidity Ratio of Amihud* (2002) is estimated as per Eq. (1). As the illiquidity measure is bounded below by zero, a larger value denotes higher illiquidity. Graphs 1 and 2 plot the daily return and daily Illiquidity measure of the ISE-100 index, respectively. According to these graphs, both series are marked by volatility clustering and become highly unstable during the 2008 global crisis. Interestingly, illiquidity seems persistent, but at the same time, it is time varying and spikes in financial downturns.



Graph 1. ISE-100 Return: 2005-2012



Graph 2. ISE-100 İlliquidity: 2005-2012

4.2. Persistence and innovations of illiquidity

The level of the market illiquidity varies across equities and is highly persistent. The auto-correlation of the first-differenced ISE-100 illiquidity is 0.81 at daily frequency. We fit an ARIMA(7,1,0) to the market illiquidity and report the results in Table 1. The AR(7) specification has an R^2 of 41%, and employing a higher level of specification or other stock-market variables produces little improvement in the explanatory power of the regression.

Table 1. The Autocorrelations in ISE-100 İlliquidity

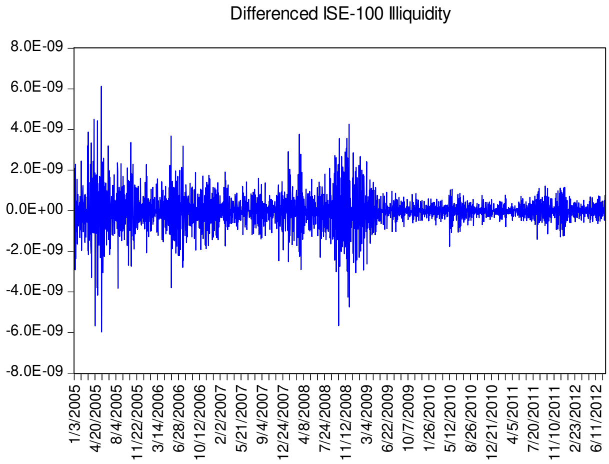
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-1.72E-13	6.61E-12	-0.026076	0.9792
AR(1)	-0.810404	0.022713	-3.568.071	0.0000
AR(2)	-0.666508	0.028731	-2.319.837	0.0000
AR(3)	-0.563923	0.031712	-1.778.277	0.0000
AR(4)	-0.419823	0.032858	-1.277.675	0.0000
AR(5)	-0.319058	0.031604	-1.009.536	0.0000
AR(6)	-0.265567	0.028485	-9.322.896	0.0000
AR(7)	-0.153093	0.022559	-6.786.406	0.0000

In order to predict the market illiquidity innovations, we run the following regression:

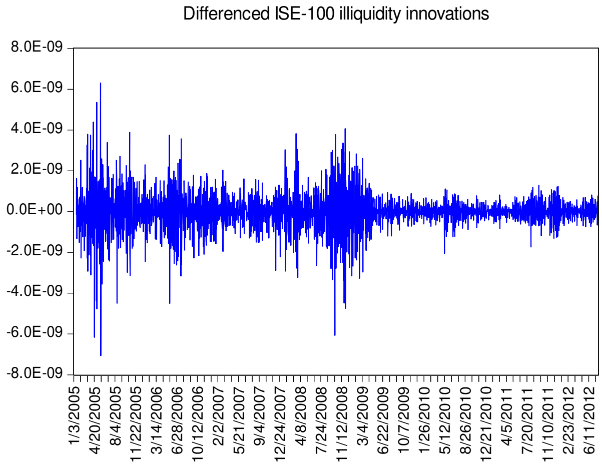
$$ILLIQ_t^M = \alpha + \beta_1 ILLIQ_{t-1}^M + \beta_2 ILLIQ_{t-2}^M + \beta_2 ILLIQ_{t-3}^M + \beta_2 ILLIQ_{t-4}^M + \beta_2 ILLIQ_{t-5}^M + \beta_2 ILLIQ_{t-6}^M + \beta_2 ILLIQ_{t-7}^M + u_t$$

where $ILLIQ_t^M$ is the first-difference of the market illiquidity. The residual in the regression is interpreted as the market illiquidity innovation, $c_t^M - E_{t-1}[c_t^M] := u_t$. The illiquidity innovations for individual stocks and portfolios are computed the same way using the same AR coefficients.

This method of computing illiquidity innovations follows from Pastor and Stambaugh (2003), Acharya and Pedersen (2005), and Lee (2009). However, they employ monthly data and fit an AR(2) specification to illiquidity series. Unlike their studies, we employ daily observations, and the serial correlations in illiquidity fades very slowly. Through the AR(7) filtering we aim to capture the autocorrelation up to one week. Graph 3 plots the market illiquidity and Graph 4 the market illiquity innovations. The measured illiquidity and illiquidity innovations are high during periods that are characterized by liquidity crises, for instance, the domestic financial crisis in 2005 and the onset of the global subprime meltdown in 2008.



Graph 3. ISE-100 İlliquidity: 2005-2012



Graph 4. ISE-100 İlliquidity Innovations: 2005-2012

4.3. Illiquidity-Sorted Portfolios

To construct illiquidity sorted portfolios, we follow a procedure similar to Acharya and Pederson (2005) and Hagströmer et al. (2011). To include a stock in the analysis, we require that price data be available at at least 100 days in a particular year. That leaves us with 80 stocks in the ISE-100 index. We form 8 illiquidity portfolios each year during the period 2005-2012, by sorting stocks based on their year y-1 illiquidities. Each portfolio consists of 10 stocks. We compute the annual illiquidity as the average of daily Amihud measures over the entire year. The process is repeated at the beginning of each year.

For each illiquidity portfolio, we compute the daily return and illiquidity of portfolio p at day t as the equal weighted average over all the stocks included in the portfolio:

$$r_t^p = \sum_{i\ in\ p} w_t^i \, r_t^i$$

$$illiq_t^p = \sum_{i\ in\ p} w_t^i \, illiq_t^i$$

We focus our analysis on equally-weighted portfolios because several studies suggest that value-weighted portfolios understate the true illiquidity of a portfolio due to the dominance of the large stock, for instance Acharya and Pedersen (2005). The ISE-100 index is taken as the market portfolio.

The portfolios are ranked in ascending order of their illiquidities. That means, the portfolio 01 consists of most liquid stocks of the ISE-100 index each year, whereas the portfolio 08 consists of most illiquid stock. Also, our portfolio formation process implies that the stocks in a particular portfolio are the same throughout a given year, but potentially varies from year to year. However, during our portfolio formation we have realized that although most stocks' illiquidity ranks change, they tend to stay in the same test portfolios. This is implies that illiquidity is persistent not only at the market, but also at individual stock level. The characteristics of our illiquidity sorted portfolios are reported in Table 2.

Table 2. Properties of İlliquidity sorted portfolios

p	*E(illiq) (%)*	*σ(illiq) (%)*	*σ(illiq. innovation) (%)*	*E(ret) (%)*	*σ(ret) (%)*	*E(exc. Ret.) (%)*	*σ(exc. Ret.) (%)*	*Corr(il_p ,il_m) (%)*	*Corr(r_p ,il_m) (%)*	*Corr(il_p, r_m) (%)*
1	0,08%	0,08%	0,06%	0,07%	1,97%	0,20%	5,61%	26%	-13%	-0,30%
2	0,36%	0,51%	0,34%	0,08%	1,90%	0,20%	5,60%	32%	-14%	0,16%
3	0,51%	0,84%	0,61%	0,06%	1,85%	0,18%	5,55%	29%	-14%	-3,94%
4	0,79%	0,89%	0,62%	0,09%	1,80%	0,22%	5,54%	35%	-15%	-1,24%
5	1,14%	2,30%	1,61%	0,10%	1,85%	0,23%	5,54%	28%	-14%	2,36%
6	1,66%	2,71%	1,96%	0,10%	1,79%	0,23%	5,55%	35%	-15%	-1,06%
7	2,75%	3,81%	2,60%	0,17%	2,08%	0,30%	5,65%	36%	-10%	-0,28%
8	7,62%	15,74%	7,71%	0,14%	1,83%	0,26%	5,53%	29%	-9%	-3,06%

Table 2 shows that sorting stocks on past year's illiquidity produces portfolios with monotonically increasing average illiquidity values. This finding confirms our previous conclusion in Section 4.1 that liquidity is a persistent variable. Moreover, we see that average illiquidity is increasing in the standard deviation of illiquidity and illiquidity innovations. Except for the last (most illiquid) portfolio, there also exists a positive relationship between expected returns and portfolio illiquidities. This implies that stocks in ISE-100 stock returns have an illiquidity premium. Thus, risk averse investors require a risk premium for holding illiquid stocks that have high variations in liquidity.

Furthermore, we find that ISE-100 stocks have correlations with the aggregate market liquidity both in terms of liquidity and returns. Interestingly, the commonality in liquidity with the market—$cov(illiq_p, illiq_m)$— and the sensitivity to market liquidity—$cov(r_p, illiq_m)$— are high and remain within a very tight range across all portfolios. This finding can implicate that some part of liquidity risk in ISE-100 may be systematic/undiversifiable. However, this is beyond the scope of this paper and should be addressed in future research.

4.4. Unconditional L-CAPM

In order to examine how liquidity risk affects the stock returns under the L-CAPM, we compute the four betas for each test portfolio using the entire daily series between 2005-2012 as in the Eqs. (5)-(8). The innovations in market and portfolio returns/illiquidities are computed using AR(7) as decribed in Section 4.2. Table 3 reports the four betas for each portfolio.

Table 3. Betas for illiquidity portfolios

Portfolio	β_1 (.100)	β_2 (.100)	β_3 (.100)	β_4 (.100)
1	0,920	0,522	-5,250	-0,006
2	0,791	2,430	-6,380	-0,047
3	0,749	4,010	-6,220	-0,069
4	0,732	5,610	-6,260	-0,097
5	0,716	6,830	-6,450	-0,128
6	0,687	12,700	-7,600	-0,199
7	0,597	20,200	-6,930	-0,340
8	0,570	30,800	-5,890	-0,581

Table 3 presents very interesting findings. First, the portfolios are monotonically decreasing in β_1 from portfolio 1 through portfolio 8. Hence, the most liquid portfolios have a much higher correlation with market returns and a higher market risk than illiquid portfolios. This is the opposite of the findings in the U.S. case (Acharya and Pedersen, 2005), where liquid stocks have lower market risk. This could be related to the fact that a few liquid stocks make up the most of the equity trade volume in Turkey.

Conversely, portfolios are monotonically increasing in β_2 and β_4. Therefore, we find that illiquid stocks also have a high liquidity risk—a high liquidity sensitivity to market returns and market illiquidity. This result is consistent with the theory and similar to the findings in the U.S. case. However, the return sensitivity to market liquidity is less straightforward. If a portfolio is more illiquid, it does not necessarily imply that it has a higher sensitivity to market liquidity shocks. Specifically, the β_3's of all the eight portfolios remain within a tight range, and suggests that this component of liquidity risk may be systematic in the Turkish equity markets.

Next, we attempt at detecting the effect of illiquidity risk on expected returns by estimating an unconditional L-CAPM. We run pooled cross-sectional OLS regressions across the eight test portfolios for the entire study period using the pre-estimated betas[1]. We perform eight different estimations of the L-CAPM and present the results in Table 4. Aiming at capturing illiquidity premiums on a daily basis, we perform the cross-sectional regressions on daily portfolio returns and illiquidity measures. Moreover, we assume that investors incur illiquidity costs once every day.

We fist assume that the risk premia of all four betas are the same and define the *net beta* as

$$\beta_p^{net} \coloneqq \beta_p^1 + \beta_p^{L1} - \beta_p^{L1} - \beta_p^{L3} \tag{9}$$

The L-CAPM becomes

$$E_t\left[r_{t+1}^p - r^f\right] = \alpha + \gamma E_t\left[c_{t+1}^p\right] + \beta_p^{net} \coloneqq \alpha + \gamma E_t\left[c_{t+1}^p\right]\alpha + \lambda\beta_p^1 + \lambda\beta_p^{L1} - \lambda\beta_p^{L1} - \lambda\beta_p^{L3} \tag{10}$$

The results of this regression are shown in line 1 of Table 4. The risk premium on the net beta is positive and significant, which lends support to the L-CAPM.

Table 4. Unconditional L-CAPM for illiquidity portfolios

Estimation	Constant	*İlliquidity*	β_1	β_2	$-\beta_3$	$-\beta_4$	*Net β*	*Net Liquidity β*
1	-0,006	-0,049***					0,01**	
	(-1,598)	(-5,166)					(2,34)	
2	0,0003	-0,050***	0,002					0,008
	(0,045)	(-5,268)	(0,192)					(-1,479)
3	0.002***	-0,05***						0,007**
	(2,678)	(-5,266)						(2,572)

[1] While Acharya and Pedersen (2005) employ a GMM (Generalized Method of Moments) in their cross-sectional regressions, we employ an OLS methodology.

4	0,01***	-0,047***	-0,009**			
	(2,947)	(-5,057)	(-2,113)			
5	0,002***	-0,049***		0,129**		
	(2,669)	(-5,252)		(2,546)		
6	0,002	-0,04***			0,173	
	(0,409)	(-4,619)			(0,248)	
7	0,002***	-0,0501***				0,007**
	(2,797)	(-5,267)				(2,573)

Notes: ***, **, * denote statistical significance at 1%, 5% and 10%, respectively.

Next, we want to isolate the effect of aggregate liquidity risk on returns and define the *net liquidity beta* as

$$\beta_p^{Lnet} \coloneqq \beta_p^{L1} - \beta_p^{L1} - \beta_p^{L3} \tag{11}$$

The L-CAPM becomes

$$E_t\left[r_{t+1}^p - r^f\right] = \alpha + \gamma E_t\left[c_{t+1}^p\right]\alpha + \lambda_1\beta_p^1 + \lambda_L\beta_p^{Lnet} \tag{12}$$

The results of this regression are given in line 2 of Table 4. The risk premia on both betas are positive, and the premium on the net liquidity β is four times as high as that on β_1. This result suggests that liquidity risk may matter more than market risk, but both coefficients are insigificant. However, the insignificance can be related to the multi-collinearity problem. As pointed out by by Acharya and Pedersen (2005) and Lee (2011), the correlations between the L-CAPM betas are high, and the cross-sectional L-CAPM regressions are subject to the multicollinearity problem. Line 3 of Table 4 drops β_1 and re-estimates the model with the net liquidity β. Then the coefficient on the net liquidity β becomes positive and significant.

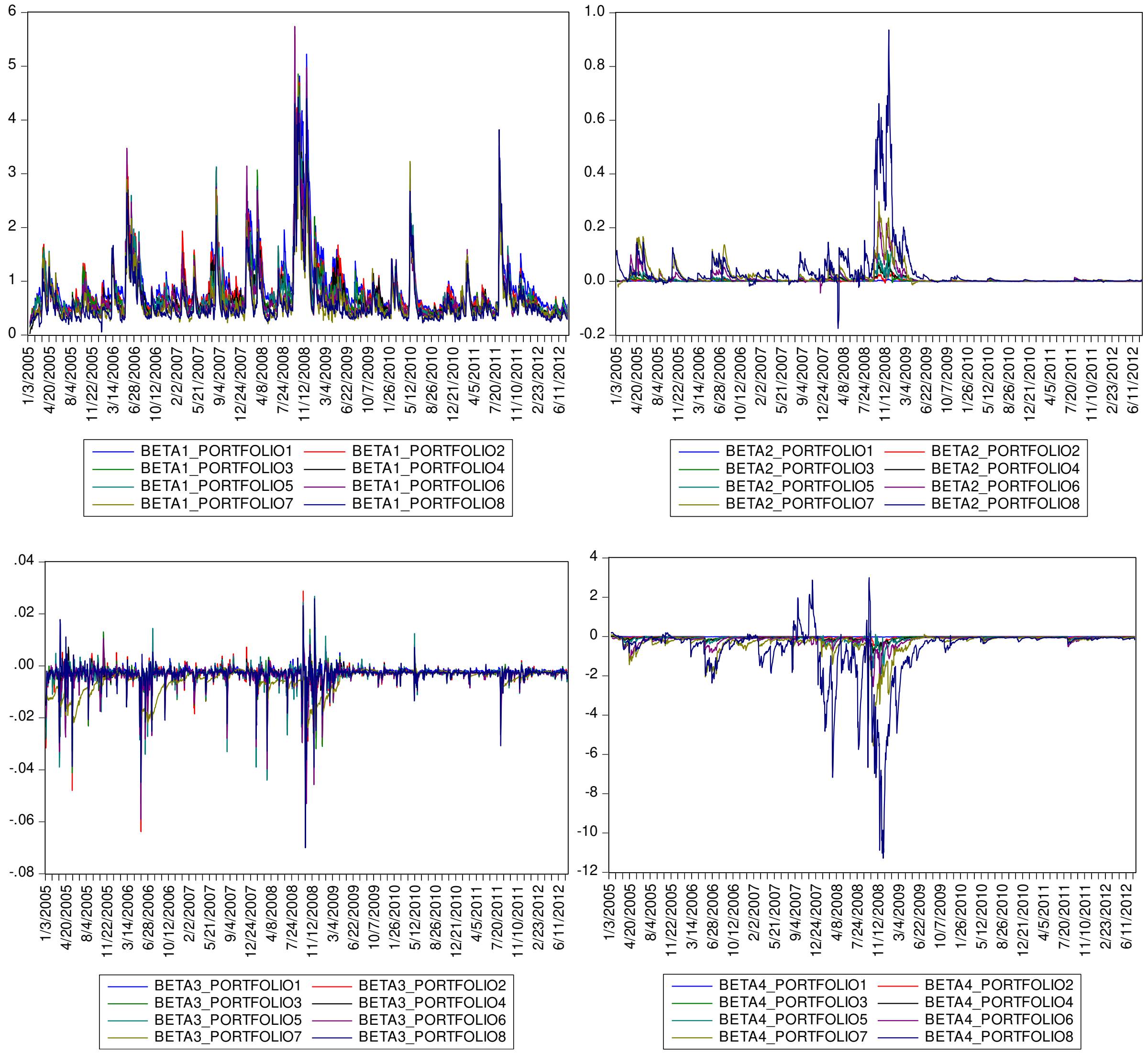
In order to alleviate the problem of multicollinearity, univariate regressions are run for each β separately. Lines 4-7 of Table 4 present the findings. β_1 is negative, so daily returns are a decreasing function of market risk. We also see that all liquidity betas, except for β_3 are strongly significant and positively affect stock returns. Hence, investors do not seem to pay a premium for the return sensitivity to market liquidity (cov(r_p, $illiq_m$)) on a daily basis. Furthermore, we find that across all estimations, the illiquidity level negatively affects daily returns. This contradicts the positive relationship between illiquidity and returns under the L-CAPM in the U.S. case in Acharya and Pedersen (2005).

4.5. Conditional L-CAPM: Diagonal VECH

In this section, we estimate a conditional version of the L-CAPM in order to capture the time variation of liquidity risk. We allow for conditional variances of innovations in illiquidity and returns, as well as conditional covariances between these series. In order to construct the L-CAPM regression, we estimate adequate ARIMA-GARCH models for the return and illiquidity series of the market and test portfolios. We find that for each series, all GARCH coefficients are statististically significant. We check the fitted models with standardized residuals and their squared processes, and we see that the Ljung-Box statistics are insignificant at the 10% level. The ARCH test on the squared residuals indicate that there are no ARCH effects left.

Using the residuals from the fitted ARIMA-GARCH models for each each series of returns and illiquidity, we estimated the conditional covariances in Eqs. (4-7) using the bivariate Diagonal VECH model. We employ the Maximum Likelihood (Marquardt) method in our estimations. We then compute the betas by dividing the covariances by the variance of difference in market return and market illiquidity measure. Graph 5 shows that whereas β_1 and β_2 generally take positive values, β_3 and β_4 take negative values. Furthermore, all betas jump and become highly volatile during the 2008 global economic crisis. β_4 takes the highest values of all betas, which means that illiquidity sensitivity to market returns may be the most important component of illiquidity risk.

Graphs 5. Time-varying betas



We also observe that although market risk is extremely volatile, all three components of illiquidity risk (β_2, β_3, β_4) have been rather stable since 2010.

Finally, we run pooled cross-sectional OLS regressions across the eight test portfolios using the pre-estimated betas. As in Section 4.2, estimate the L-CAPM regression

$$E_t\left[r_{t+1}^p - r^f\right] = \alpha + \gamma E_t\left[c_{t+1}^p\right]\alpha + \lambda\beta_p^1 + \lambda\beta_p^{L1} - \lambda\beta_p^{L1} - \lambda\beta_p^{L3}$$

We find that while net β in line 1 of Table 6 is insignificant, both β_1 and the net liquidity β are significant in line 2. β_1 is negative while the net net liquidity β is positive. This suggests that aggregate liquidity risk has a higher premium than market risk. When excess returns are regressed on the net liquidity *β,* the effect reduces in magnitude but stays positive and significant. We also find across all estimations that illiquidity negatively and strongly affects daily returns.

Checking for collinearity, we find very high correlations among the four betas (Table 5). This makes it statistically very difficult to measure the individual effect of each risk.

Table 5. Beta Correlations

	β_1	β_2	β_3	β_4
β_1	1,000			
β_2	0,671	1,000		
β_3	-0,372	-0,402	1,000	
β_4	-0,679	-0,800	0,417	1,000

Notes: Average correlation of the eight portfolios is reported.

In order to minimize the multicollinearity problem, we run univariate regressions on each *β* separately. Lines 4-7 of Table 4 present the findings.

We see that while the market risk (β_1) is insignificant, all liquidity betas are strongly significant. β_2 and β_4 are positive, which means that investors require a return premium for portfolios that become illiquid in times of poor market return and high illiquidity. On the other hand, β_3 is negative. Hence, investors do not seem to require a premium for the return sensitivity to market liquidity (cov(r_p, $illiq_m$)), and returns are lower when β_3 is higher. The results show that from all three liquidity channels β_2 has the highest impact. This is different from the findings of Acharya and Pedersen (2005), which implies that liquidity impacts differ in Turkey compared to the U.S.

Table 6. Conditional L-CAPM for illiquidity portfolios

Estimation	Constant	*Illiquidity*	β_1	β_2	$-\beta_3$	$-\beta_4$	*Net* β	*Net Liquidity* β
1	0,002***	-0,04***					0,0006	
	(3,647)	(-4,459)					(1,134)	
2	0,004***	-0,061***	-0,002**					0,003***
	(5,033)	(-5,57)	(-2,006)					(3,59)
3	0,003***	-0,061***						0,003**
	(5,522)	(-5,558)						(3,253)
4	0,004***	-0,0372***	-0.001					
	(4,806)	(-4,268)	(-1,333)					
5	0,003***	-0,059***		0,039***				
	(5,87)	(-5,209)		(2,721)				
6	0,004***	-0,036***			-0.206**			
	(6,218)	(-4,177)			(-2,116)			
7	0,003***	-0,06***				0.003**		
	(5,544)	(-5,552)				(3,239)		

Notes: ***, **, * denote statistical significance at 1%, 5% and 10%, respectively.

5. Conclusion

This paper examines the impact of illiquidity and liquidity risk on expected stock returns in the Turkish stock markets. Using daily data of the ISE-100 stock index from 2005 to 2012 and Amihud (2002) illiquidity measure, we test the liquidity-adjusted capital asset pricing model (L-CAPM) of Acharya and Pedersen (2005) for 2005-2012. We estimate both an unconditional and a conditional version of the L-CAPM model and perform OLS cross-sectional regressions on illiquidity-sorted test portfolios. We find supporting evidence that both illiquidity level and liquidity risk have a significant impact on the cross-section of stock returns in Turkey.

Our results indicate that while illiquidity is persistent and lowers stock returns, liquidity risk is significantly and positively priced. The most dominant liquidity risk in terms of illiquidity premia is the covariance between security's illiquidity and the market illiquidity (β_2). The strong inter-relationship between the market liquidity and the liquidity of individual stocks suggests that market wide shocks on the Istanbul Stock Exchange might quickly affect every stock in this market. Hence, liquidity commonality can create a systemic risk in which case liquidity shocks can be perfectly correlated across all stocks. Moreover, the security's illiquidity sensitivity to market returns (β_4) is also positive and significant. These results are different from the U.S. case, where Acharya and Pedersen (2005) find that the most dominant liquidity risk is β_4.

Based on the results of this paper, we conclude that liquidity risk is a key driver of returns in the Turkish equity markets. We pave the way for future research, providing interesting implications for investors, risk managers and regulators. As liquidity risk is priced, investors should incorporate it into their trading and hedging strategies to improve their risk profile, and increase their investment returns. Furthermore, a deeper understanding of systemic liquidity risk is vital for regulatory authorities to design improved regulations against systemic shocks. As a next step, it can be of interest to explain illiquidity impact with a Fama-French approach controlling for factors such as size, book-to-market-ratio, momentum and P/E factor. It would also be interesting to analyze the return-illiquidity relationship with different illiquidity measures, and to investigate the sensitivity of the results to different liquidity proxies. Finally, future studies can extend our research to other asset groups and examine the drivers of systemic liquidity risk, a concept which is not yet well understood in the emerging world.

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